From Pre-Conceptions to Theories: How Middle School Student Ideas about Predictive Text Evolve after Interaction with a New Software Tool

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Abstract

We developed Next Word Adventure, a new software tool that helps middle school students understand n-gram models. Students see how n-grams are constructed from sentences that they provide to the software. Students can modify the n-value and see its effect on the n-gram that is created. A dynamic diagram helps students grasp the statistical processes and how data and parameter choices influence outcomes. In a study with 48 students from 6th to 8th grade, survey items revealed pre-conceptions, such as equating word prediction functionality with internet searches and overestimating such capabilities. After interaction with our software tool, 31 students recognized n-grams' dependency on statistical data rather than assuming a cognitive understanding of text. They appreciated the significance of the *n* parameter in enhancing prediction accuracy. The study suggests the software was effective in helping students developing a probabilistic model of text prediction.

CCS Concepts

• **Applied computing → Interactive learning environments**; • **Computing methodologies → Artificial intelligence**; **Machine learning**.

Keywords

AI Education, Predictive Text, Software Tool

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1 Introduction

As artificial intelligence (AI) increasingly influences various aspects of daily life, cultivating AI literacy among younger generations has become imperative. This literacy equips children with the necessary skills to navigate and shape a technology-driven world [6, 9]. Educational guidelines and standards for K-12 AI education highlight the increasing need to prepare students to navigate and contribute to a technology-driven world [14]. Organizations like [2] and [10] emphasize the need for students to not only understand data but also to control, manipulate, and ethically use it, as AI and machine learning increasingly rely on data over traditional coding [4].

However, AI concepts often rely on complex models that are typically opaque in nature, making them difficult for learners to understand and examine. In response "glass box" models are gaining prominence as essential in AI education. These models are designed to be transparent and interpretable, enabling users to observe the transformation of inputs into outputs and providing insight into the internal workings of the systems. This transparency is vital for educational tools that aim to demystify AI, aligning with pedagogical objectives of fostering deep understanding and promoting active learning [3, 12].

Addressing these challenges requires tools that do more than teach—they must actively engage students in learning processes rooted in established educational theories like Jean Piaget's constructivist approach [11]. This theory posits that true knowledge is constructed through active engagement with one's environment and that effective learning emerges not from passive information reception but through active experimentation. This approach also underpins our AI Chef Trainer, an educational web application that allowed students to construct their knowledge by experimenting with their own data inputs and observing the results and understand the learning dynamics of the system [8].

Building on these principles, we developed Next Word Adventure, an educational web application that embodies the "glass box" approach by allowing students to input their own data and interact directly with the decision-making process of n-gram models. Through this hands-on experience, students learn foundational concepts of natural language processing (NLP) by observing firsthand how n-grams predict the next word based on the data they encode. In today's advanced language models, understanding these basic yet powerful models is essential. While n-grams lack context understanding—which may cause errors in different contexts—they clearly demonstrate how data shapes AI decisions and reveal the statistics underlying these predictions. This study aims to address:

1. To what extent does using Next Word Adventure change students' understanding of how n-grams work?

2. How do middle school students perceive the transparency in AI after interacting with Next Word Adventure?

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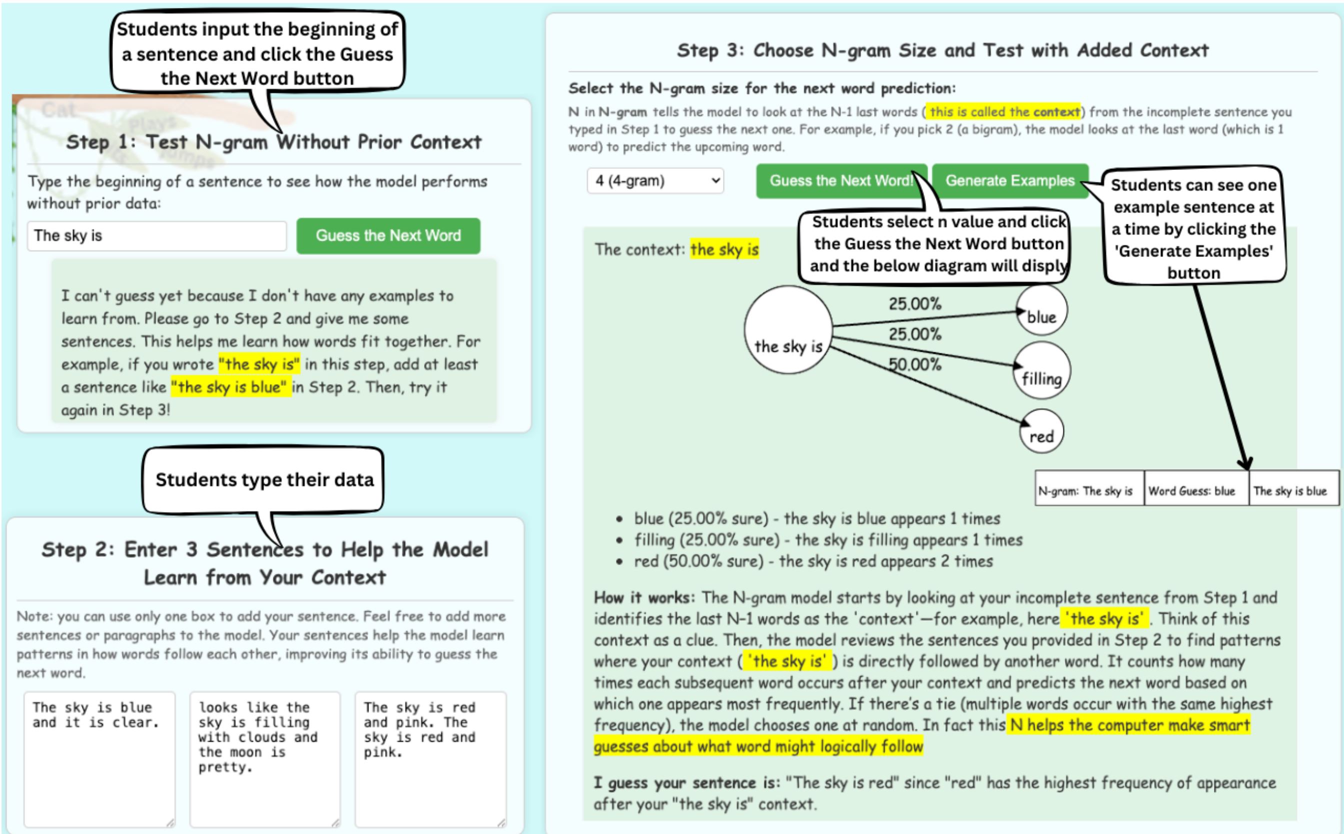

Figure 1: Next Word Adventure's Page 2

2 Background

Language has evolved from a simple communication tool to a critical interface for interacting with artificial intelligence (AI) technologies that influence our daily lives, such as virtual assistants and predictive text systems [5, 7]. Understanding these systems is crucial, especially for children in an AI-rich environment.

The foundation of modern NLP was established by pioneers like Andrey Markov and Claude Shannon through the development of n-grams, which predict word sequences based on statistical dependencies [13, 17]. Despite the complexity of modern predictive systems like neural networks, n-grams provide essential insights into sequence prediction, valuable for educational purposes where simplicity and clarity are key [15].

The MarkovChainDemo, developed by Touretzky, exemplifies this by using 'The Wizard of Oz" as a foundational text to demonstrate Markov chain text generation. It starts with an initial word and selects subsequent words based on their occurrence frequencies. This process is visualized through a table that lists each word, its potential successors, and the frequency of these occurrences, enabling users to generate text either automatically or manually [15]. Continuing the tradition of simplifying complex models, this study introduces Next Word Adventure which demonstrates how statistical models like n-grams predict the next word. As our study suggests, this tool deepens students' understanding of basic probability and statistics, foundational for advanced AI and machine learning studies.

3 Software Design and Implementation

3.1 User Interface

The user interface is organized across two main pages that guide students through the principles of n-grams. The frontend was built using HTML for structure, CSS for visual styling, and JavaScript for interactive elements.

- **Initial page** This page serves as an introduction to the software, where students input their personal data including their name and grade to initialize their personalize interactive sessions. To minimize cognitive load, the page features five preloaded examples that showcase the software suggests the next word, providing a relevant introduction to the core concept.
- **Main page** This three-step page is the core of the interactive experience (Figure 1):
  - **Step 1:** Students input the beginning of a sentence and click the "Guess the Next Word" button. If no prior data from the student exists, the model indicates its inability to make a prediction, emphasizing the critical role of data

Table 1: Proportion of Students Selecting Each Predefined Sentence. Words in blue shows the target next word (ordered as in the Drop-Down Menu)

Sentence	Total Responses
The earth is round	29
The Stegosaurus's brain was as small as a walnut	18
Giraffes have the same number of neck bones as human	8
The most popular sport in the world is soccer	12
Anime characters often have colorful hair	19

in forming accurate predictions and setting the stage for understanding predictive modeling.

– **Step 2:** In this step, students contribute sentences to enhance the system's accuracy. The n-gram model then adapts to predict solely based on this data, demonstrating the significant impact of context in shaping text predictions and illustrating the model's responsiveness to new information.
– **Step 3:** This final step allows students select different values for n (2, 3, or 4), exploring how changing these parameters influences the model's suggestions. An interactive diagram displays the probabilities of potential next words and shows the impact of word frequency on predictions, helping students connect statistical likelihood to their own data.

3.2 Software Architecture

Next Word Adventure was developed using the Flask framework, a choice reflecting its flexibility and suitability for rapid development of web applications [1]. The backend, implemented in Python, handles HTTP requests and dynamically delivers content. The system employs NLTK's Punkt tokenizer, part of the broader NLTK library, to accurately segment student-inputted text. This step is critical for constructing personalized n-gram models that form the core of the predictive text functionality. This tokenizer choice is particularly beneficial for its robust handling of diverse punctuation and capitalization, ensuring that tokens are accurately extracted for n-gram model construction. Once tokenized, these inputs are used to calculate the raw frequencies of word sequences, which are then transformed into probabilities through a normalization process. This involves dividing the count of each word sequence by the total occurrences of the starting n-gram sequence, thereby adapting the model continuously as new student data is entered. (Source code is available on GitHub [16]).

4 Study Design

Next Word Adventure was tested during two after-school sessions at a STEM charter school in a major Texas city, involving 6th to 8th graders in Fall 2024. Each session featured six stations, with participants engaging with the software for 10–20 minutes each. IRB approval was obtained, along with parent consent and student assent for all participants. Embedded survey items and a post-interaction survey were administered.

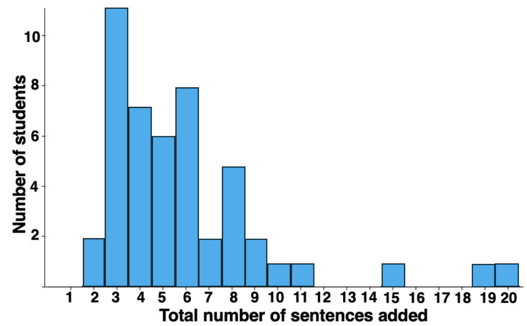

Figure 2: Histogram of total number of sentences added by 48 students in step 2. In total, students added 299 sentences

Before interacting with the software, students were not formally introduced to the concept of n-grams. Instead, they were introduced to n-grams by linking the concept to everyday technologies like predictive text on smartphones, a familiar context that made the abstract concept more tangible and engaging. However, when students asked questions while interacting with the main page, we highlighted the significance of the variable n, which determines the number of sequential words considered when predicting the next word, acting as a "clue" for pattern recognition in predictive text. This approach demystified the computational logic behind n-grams, making it understandable.

5 Results and Discussion

This section outlines key insights from interaction logs, audio/screen recordings, and post-survey responses of 48 students (20 sixth graders, 18 seventh graders, 10 eighth graders), with 42 completing the post-interaction survey.

5.1 Student Engagement

In our analysis of students engagement with Next Word Adventure, we examined the frequency of sentence selection from the initial page and the distribution of tests across different N values. Out of 48 participants, 47 interacted with at least one predefined sentence. Notably, "The Earth is," which was the first sentence in the predefined list, was selected 48 times, chosen by over half of the participants as shown in Table 1. In contrast, "Giraffes have the same number of neck bones as" was the least frequently selected, attracting only 8 students, who chose it a total of 11 times.

Figure 2 shows that most students (31 out of 48) added between 3 to 6 sentences in Step 2, with the most common entry being 4 sentences per student. This distribution indicates that students typically engage with a moderate amount of data, with fewer testing the model's limits with higher data entries. Furthermore, except for two students, all successfully completed Steps 1 to 3, achieving a high task completion rate of approximately 95.83%.

5.2 Students' Initial Perceptions of N-gram Mechanisms

This section analyzes students' initial perceptions of n-gram predictions ***before*** using the software, based on their responses to the prompt: "How do you think the N-gram guessed the next word?" Key themes identified include:

External Data Sources (12 responses) Some believed the model accessed external information to make predictions. Common pre-conceptions included data retrieval from "Google," "different browsers," and "the internet." Examples included "Collects the info from different sources that has a similar sentence structure and chooses the correct word for it"; "I think it gets other information that other people use or search up. It gives you the information from other people"; "The N gram uses Google"; "it used trustable websites."

Overestimated Abilities (11 responses) Some students attributed cognitive processing abilities to n-grams, suggesting they recognize patterns or analyze content meaningfully. Examples included: "It guessed it by the topic"; "The meanings and usual connotations of certain words and phrases." Responses in this category attribute reasoning, or understanding capabilities to n-grams, such as recognizing patterns in a way that implies understanding, or making logical guesses based on content analysis. Examples were "I think it used the characteristics of the earth"; "It looked at pictures of the thing we are looking at and sees what adjective matches."

Creative but Incorrect Theories (9 responses) This category includes imaginative yet incorrect theories about n-gram operations. Examples included "The N-gram uses a specific coding language, or it is programmed. Then, it stores all the words into its microchip or the lexicon of the computer"; "I think it used an averaging process that helps it choose what the answer is"; "N-gram probably guessed the next word using common items that are known as small which in this case a walnut"; "It probably used the shape of the word."

A few students showed a partial understanding of the model. Two examples were "It looked at many samples and used the word combination that popped up most frequently"; "It used data from past experiences"; and "I think the N-gram was trained on actual human conversation and noticed patterns.

5.3 Student Perceptions on N-gram after Interaction

This section shows changes in students' understanding of the n-gram model ***after*** interaction with the software, based on responses to post-interaction survey and embedded questions.

5.3.1 Conceptual Understanding of the N-gram Model. Student's responses to the prompt, "Do you think the model really understands the sentences you added? Why or why not?" revealed two main changes in perceptions of students.

Statistical Analysis of Context (19 responses) Many students recognized that the model operates statistically rather than understanding content. They noted it uses repetition and probability to predict words, e.g., "It looks at how much that sentence or word is repeated. If there is more of that, then it'll have a higher chance of putting that word into the result"; "It uses probability and the most used words to decide what word will most likely come next. If multiple values are the same, it decides randomly"; "N-gram models know what comes next from calculating percentages and using info/sentences to try to know what will be next."

Table 2: Student responses to "What happens when you change the N-gram size from 2 to 3?" Correct answers are both A and C. One chose three options (A,B, C)

Choices	Total Responses
A. The model looks at more words together	29
B. The model's predictions become less accurate	6
C. The model's predictions might become more accurate because it has more context	24
D. I am not sure	3

Conceptual Understanding (12 responses) Several students highlighted the model's limitations, understanding that it processes inputs without grasping their meaning, e.g., "the model seemed to use the words I put in, but didn't try to figure out what it actually meant"; "No, because I put the sky is 'not blue' and it said there was a 100% chance the next word(s) would be 'not blue,' but if it really understood the sentences I added then it would have said the sky was blue. I believe it relied more on what word came after."

Together, these 31 responses–19 and 12– show the model's reliance on statistic rather than cognitive understanding. Misconceptions persisted after interaction among three students. Responses were "yes because the ai is really advanced"; "Yes. It should have that microchip or sense to understand different words." Also, six simply said "No" or "yes."

5.3.2 The Role of N value. In an exploration of students' understanding of how increasing the n-gram size from 2 to 3 affects a model's behavior, we posed the question, "What happens when you change the N-gram size from 2 to 3?" This aimed to assess their grasp of changes in context size and performance. As shown in Table 2, the majority of students correctly identified that increasing the n value from 2 to 3 allows the model to analyze more words together and potentially enhance prediction accuracy due to greater contextual awareness. A few students showed mixed understanding: Six students recognized that more words in the context could lead to more accurate predictions by choosing both options A (increased word analysis) and C (enhanced accuracy). Two students chose both options A (increased word analysis) and B (potential decrease in accuracy), indicating uncertainty about the outcome.

Further inquiry into the significance of the n value, we asked, "What does the n number show us about how the model makes guesses? Which n do you think would be best for guessing the next word?" This prompted diverse responses:

Understanding of N as Context Size (11 responses) Some students recognized that the n indicates how many words are considered for making predictions, often associating higher n values with increased prediction accuracy. Examples included "The higher number of words you let it scan, the more accurate it becomes;"'N shows the number of words it uses to identify the appropriate ending to a sentence. A bigger n would be good for guessing words since it has more context to make more accurate guesses."

Table 3: Student responses to "If the N-gram model has a high probability prediction but is wrong, what does this tell you?" The correct answer is option B.

Choices	Total Responses
A. The model is broken	4
B. High probability indicates frequency in the training data, not certainty	24
C. The model is guessing randomly	14
D. I am not sure	4

Table 4: Student responses to "What does a probability next to a predicted word tell us?"

Choices	Total Responses
A. How frequently the computer uses the word	25
B. How sure the computer is that this will be the next word	25
C. How many letters are in the word	3
D. I am not sure	1

Table 5: Student responses to "If an N-gram model predicts the wrong word and causes a misunderstanding, who should be responsible?"

Choices	Total Responses
A. The developer who designed the model	16
B. The user who relied on the prediction	7
C. Both the developer and the user	6
D. Neither it's just how the model works	13

Preferences for Higher N Values (6 responses) Students expressed a preference for larger *n* values, often citing the potential for more accurate predictions due to increased data. One student noted, "4, the software will look at more words, " indicating a preference for a broader lexical scope to improve prediction quality. "I think the higher N is the more accurate the guess would be. I think this because the computer has more data to work with, so it will naturally make more accurate predictions."

5.3.3 Student Perceptions of Probabilistic Predictions in N-gram Models. To assess students' grasp of probabilistic predictions models, we asked, "If the N-gram model has a high probability prediction but is wrong, what does this tell you?" Insights from this analysis are crucial for identifying misconceptions. As shown in Table 3, most students recognized that a high probability prediction indicates frequent occurrences in the training data, not guaranteed accuracy, revealing a mature understanding of the probabilistic nature of machine learning. Yet, some students showed mixed understanding by selecting option combinations that included both misconceptions and partial understanding, e.g., (A, C) and (A, D). To explore deeper, we asked, "What does a probability next to a predicted word tell us?" as shown in Table 4, most responses indicated that probabilities reflect the likelihood of a word's occurrence based on past data.

5.4 Student's Perceptions about Accountability in AI Use

To understand students' views on AI accountability when n-gram models mispredict, we asked: "If an N-gram model causes a misunderstanding by predicting the wrong word, who should be responsible?" Table 5 reveals that 16 out of 42 students held developers responsible, highlighting the need for reliable AI models with minimal errors. Another 13 recognized acknowledged that errors are inherent in AI technologies. This range of views underscores the importance of educating about AI's realistic capabilities and limitations.

Further exploring transparency in AI, we asked, "Do you think it's important for AI tools and tools like N-gram models to be transparent about how they make predictions?" The responses categorized into several themes (7 responses were yes and one said "No because people really won't care."):

Understanding and Building Trust (15 responses) Most students agreed that transparency is crucial for enhancing understanding and trust in AI systems. They noted that it helps demystify AI operations and enables effective user interaction, with examples like "It helps the person understand how AI helps them everyday"; " because it helps them get a better understanding of the software so they know how to use it properly"; "so we can learn and teach"; "Yes because we need to know where the info is from"; "so the user can understand."

Accuracy and Correctness (8 responses) Students also viewed transparency as vital for verifying AI's accuracy and reliability. They expressed that knowing how predictions are made allows for the confirmation of their correctness, as seen in comments such as "so we can make sure that the AI is making correct decisions"; "It is important so it can give accurate answers"; "as otherwise they will be hard to fix if they go wrong"; "because it can be very accurate but sometimes not as much"; "we can make sure that the AI is making the right decisions."

Bias and Fairness (6 responses) Students recognized that transparency is crucial for both understanding operations and addressing biases in AI models. Examples included " because then it might be inaccurate"; "Yes so the consumer understands if the AI has bias" and "Yes, N-gram could be wrong"; "No because they need to provide the most relevant information and the most used words"; "Yes, N-gram could be wrong. "

5.5 A Thematic Analysis of Students Sentences

Analysis of 251 unique sentences (299 total) from student interactions in Step 2 revealed the below themes.

Personal and Social Expressions This theme captures sentences that reflect personal preferences, social interactions, or individual actions. Examples are "My favorite sport involves a bat and a ball"; "My favorite thing to do is play basketball"; "I like to play games"; "I like to eat ice cream"; "how can i swim" ; "the most popular band is ENHYPEN"; "ENHYPEN has the best music"; "Peter likes to watch tv."

Descriptive, Factual, and Natural It includes sentences that provide descriptions of the physical world or specific factual information. Examples are: "The rock is hard and flat"; "The trees are green and brown"; "The ocean is blue because of the sky"; "bananas are yellow"; "The Earth is a planet"; "Real Madrid is a soccer team."

Inquiry and Information Seeking In this category, students posed questions or seek specific information. Examples are "What is the computer do"; "How to spell belin?"

5.6 Student Example

An eighth grader began exploring the software by interacting with two predefined sentences: "The Earth is" and then tested "The most popular sport in the world is." Then, they answered the software prompt about how the model suggests the next word, initially believing that "The N-gram uses a specific coding language, or it is programmed. Then, it stores all the words into its microchip or the lexicon of the computer. Next, it reads the sentence, it tries to understand what's going on by identifying every word. After it does that, it tries to find the best word for that sentence." Upon navigating to the main page, the student entered the phrase "Alex is so" (using "Alex," a pseudonym to ensure privacy). In the second step, the student added sentences such as "Alex is so cool"; "Alex is so goofy"; "Alex is so nice" to observe how the model adapted to these inputs. Initial tests with N-values of 4 and 2 showed equal probabilities (33%) for the suggested words "cool," "goofy," and "nice." The student then repeatedly added "Alex is so cool" six times to the dataset and noted a significant preference for "cool," with a probability of approximately 80% when tested with N=3. Further experimentation involved modifying the base phrase to "he," and adding contextually rich sentences like "Alex is so goofy he likes anime" and "Alex is so nice that he likes to give me Dosa" [Indian dish]. When these were tested with N=2, the probabilities varied, with "is" appearing 30% of the time and "likes" 70%, demonstrating how context and frequency affect prediction accuracy. Reflecting on the experience, the student summarized their understanding: "The N-gram model gets the incomplete sentence and makes complete sentences out of them. This can have a random frequency and a chance to put that word into the result. It looks at how much that sentence or word is repeated. If there is more of that, then it'll have a higher chance of putting that word into the result." In total, the student conducted ten trials using various N values. This case study showcased their growing grasp of the model's workings and their personal engagement with the software, highlighted by incorporating a friend's name in the experiments.

6 Conclusions, Limitations, and Future Work

Next Word Adventure, which embodies the "glass box" approach, was developed within the framework of Jean Piaget's constructivist educational theory to actively engage middle school students in the learning process. This is achieved by allowing them to input their own sentences and observe how n-grams are constructed from their data. A similar design principle was applied to our AI Chef Trainer; an interactive software tool that introduces children to the role of data in AI through recipe recommendations. By allowing students to contribute their own recipes in re-training process, students recognized the dependency of AI on data in terms of quantity and specificity. They also understood AI learns and adapts when provided with new data [8]. We recommend the glass box approach as a design principle for educational software tools to help young learners understand AI.

Our research questions were: To what extent does using the software change students' understanding of how n-grams work? How do middle school students perceive the transparency after interacting with the software?

A total of 48 students interacted with the software. Data show a perceptual shift among students after interaction with the software. Initially, students had various pre-conceptions about word prediction: 12 students believed that these models pull information from external sources like the internet, some attributed human-like cognitive abilities to AI, such as understanding context; and a smaller group proposed imaginative but inaccurate theories about the models' operation. Post-interaction insights from 31 of the 42 completed surveys indicate a shift towards a more accurate understanding of how n-gram models function, recognizing that these models rely solely on statistical data and do not "understand" text in the human sense. Students also acknowledged that high probability does not guarantee accuracy, reflecting a more mature approach to interpreting model outputs. This shift highlights the effectiveness of interactive educational tools in demystifying complex technologies. Altering n values and observing changes in prediction accuracy both enriched students' understanding and actively engaged them in learning. There was consensus on the crucial role of transparency in building trust, ensuring accuracy, and addressing biases in AI models, with students emphasizing transparency as essential for both operational understanding and ethical oversight. Considering student responses on the preference for higher n values for better accuracy, future AI tools for educational purposes should allow adjustable settings to deepen students' practical understanding of AI/ML modeling. Introducing n-grams to students provides essential groundwork for understanding advanced systems like LLMs, illustrating the probabilistic nature of AI through the sampling distribution of the next word. Exploring n-grams both lays the foundational knowledge of how predictions are made and also reveals their limitations, such as the lack of contextual awareness. These understandings prompts students to recognize the need for more sophisticated models like LLMs, which can generate meaningful text by integrating broader contextual information.

This study, while insightful, is limited by its small sample size; future research should include a broader demographic to enhance applicability. It also lacks a long-term learning assessment. Ongoing challenges in fully comprehending the probabilistic basis of the predictions suggest the need for enhanced curricular content that elucidates these concepts.

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